DNN Latency Sequencing: Extracting DNN Architectures from Intel SGX Enclaves with Single-Stepping Attacks

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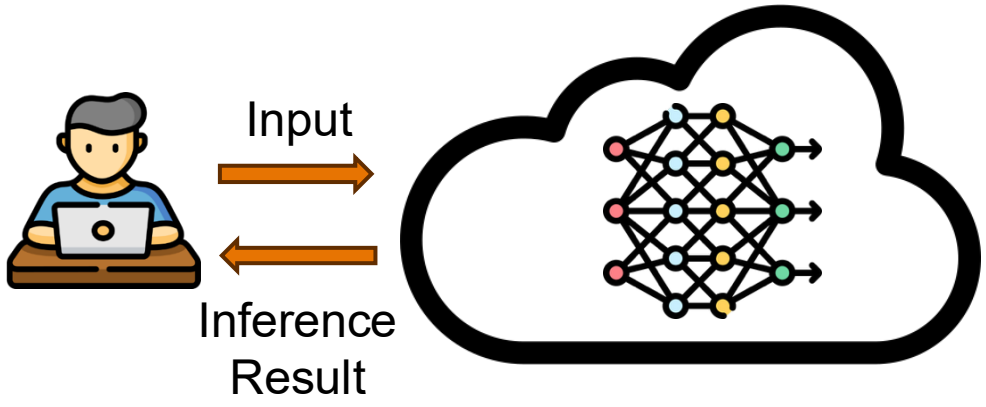

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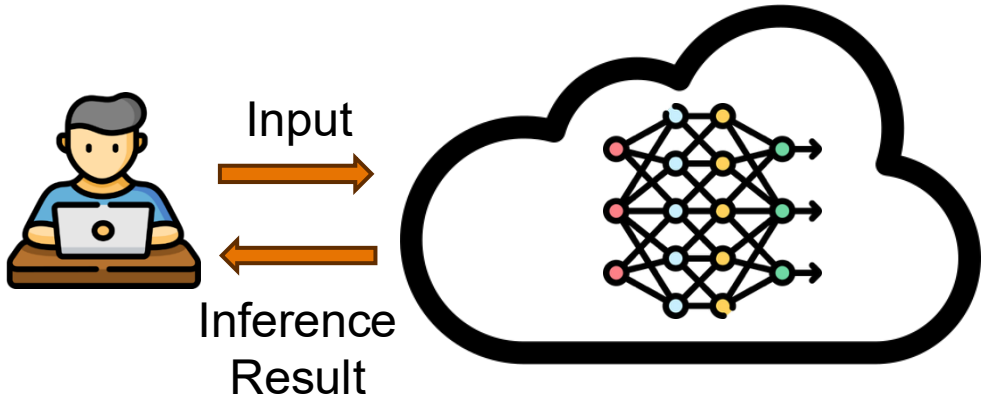
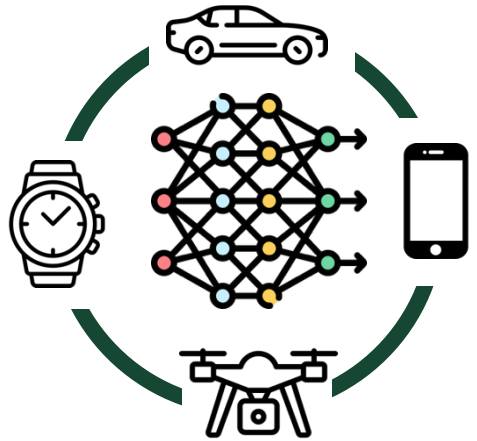


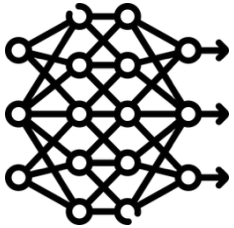
- On Device Deep Learning



DNN Models

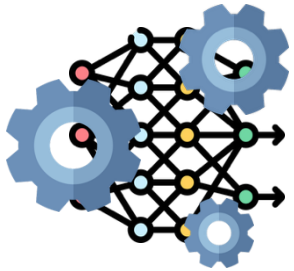
- System performance is largely determined by the DNN model

Structure



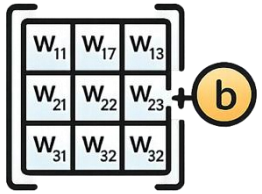
- #Layer
- Layer type

Hyperparameter



- Kernel size
- Pool size

Parameter



DNN Models

- Serve as valuable intellectual property (IP)
- Designing and training a model is computation-intensive and time-consuming

Input Acquisition & Labeling

GPU, Power, Time Cost

Domain Expertise

Model Extraction Attack: Architecture Stealing

- A type of attack to steal DNN architectures
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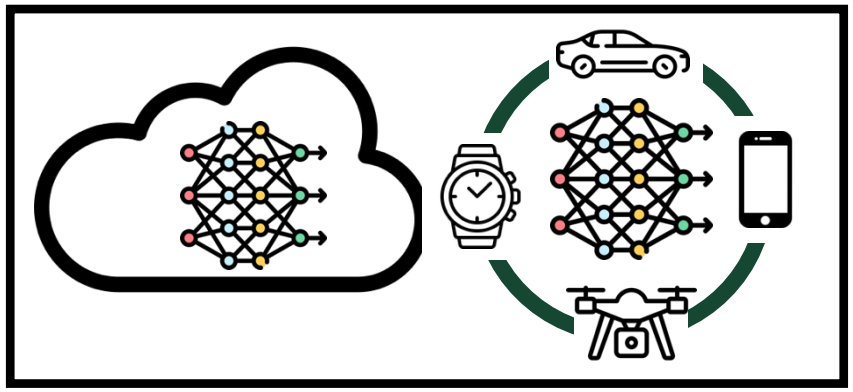
Attacker



Victim Models in Black Box

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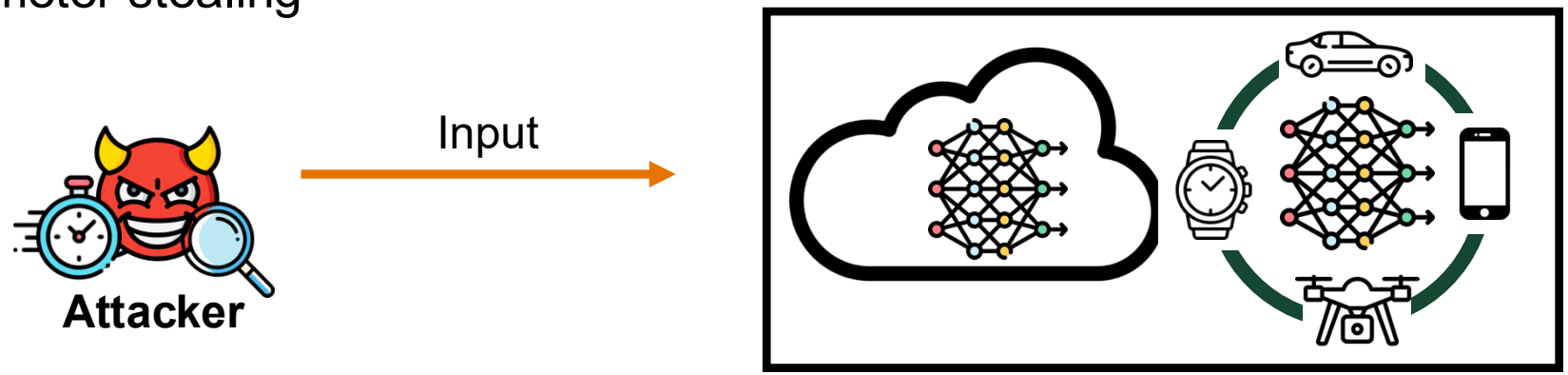

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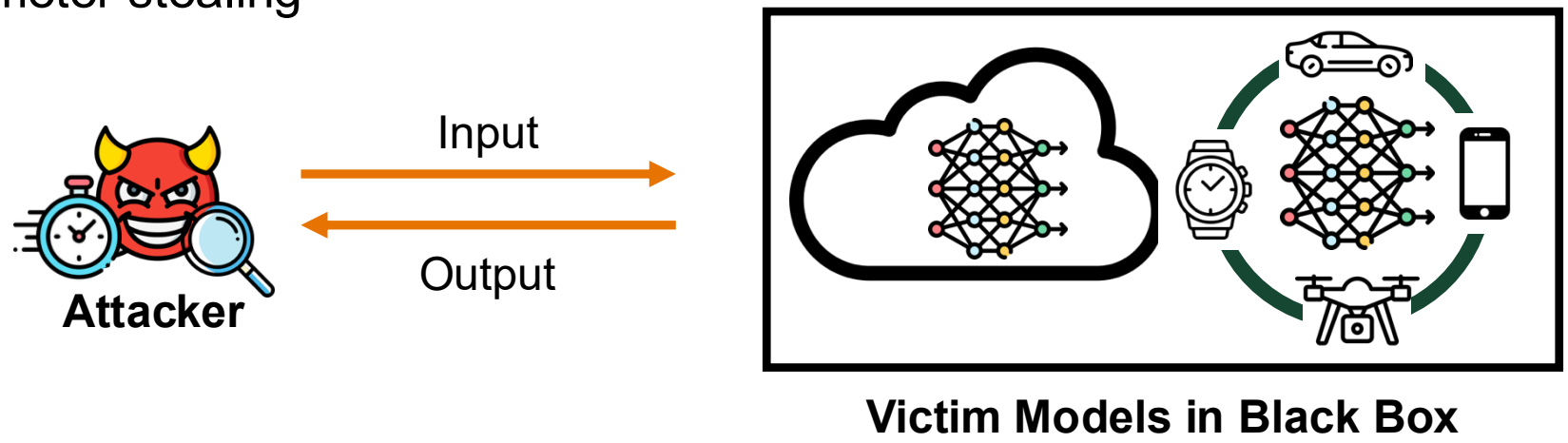

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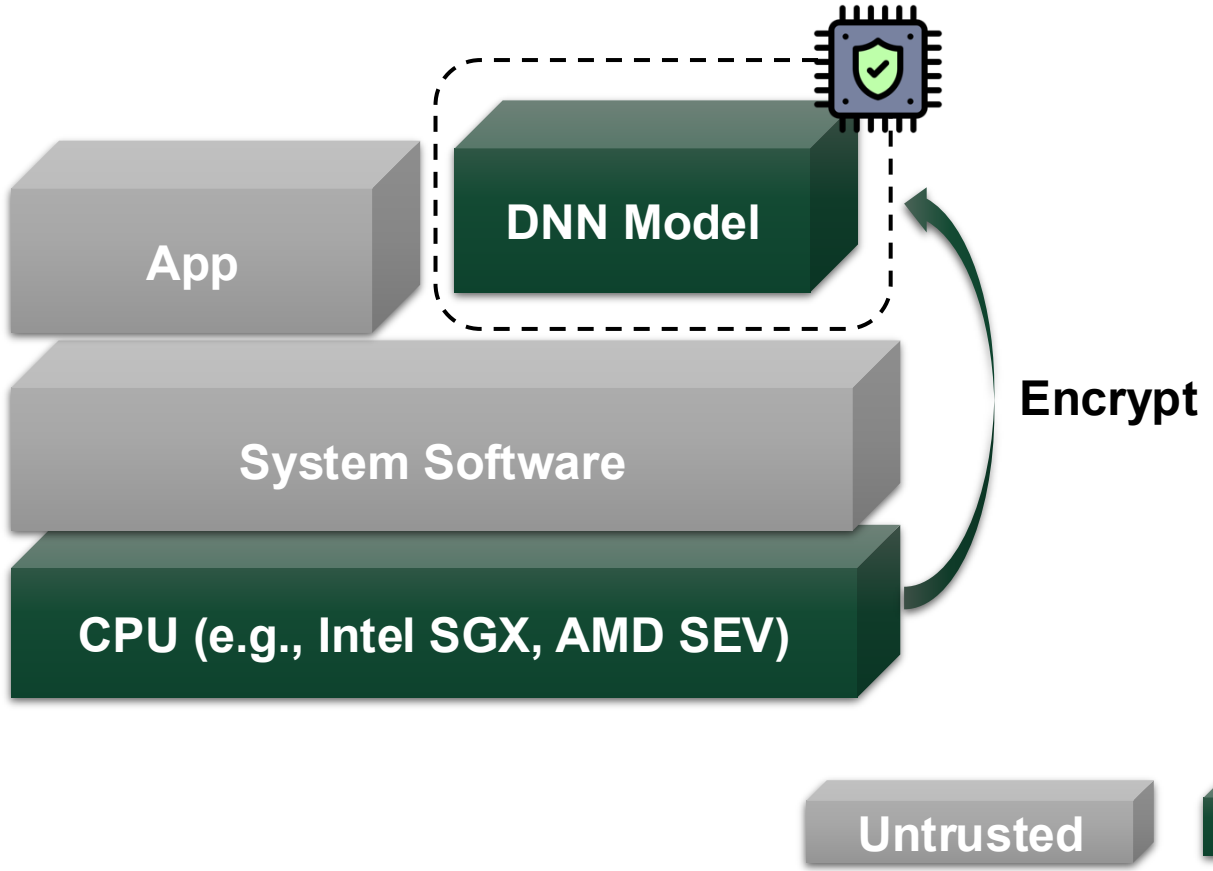
- Why it matters
  - Enables reconstruction of a similarly performing model
  - Acts as a stepping stone for follow-on attacks

Confidential AI

- Trusted Execution Environment (TEE) protects DNN models by during its processing



Single-Stepping Attacks on TEE

- TEE introduces new types of side-channels such as ***instruction latency***
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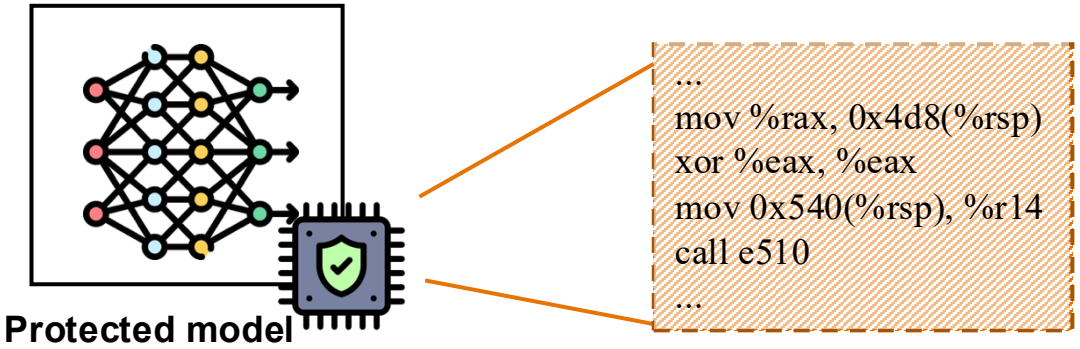

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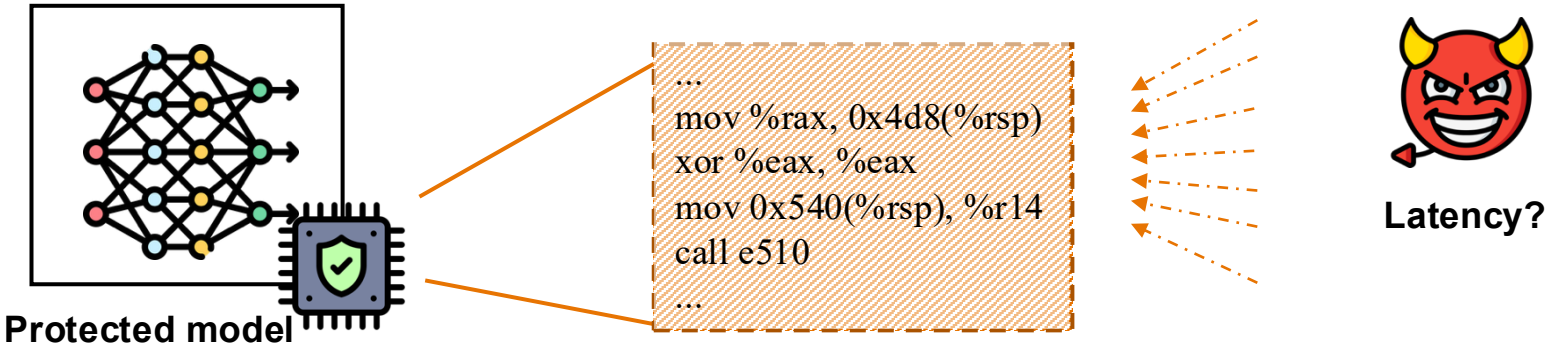

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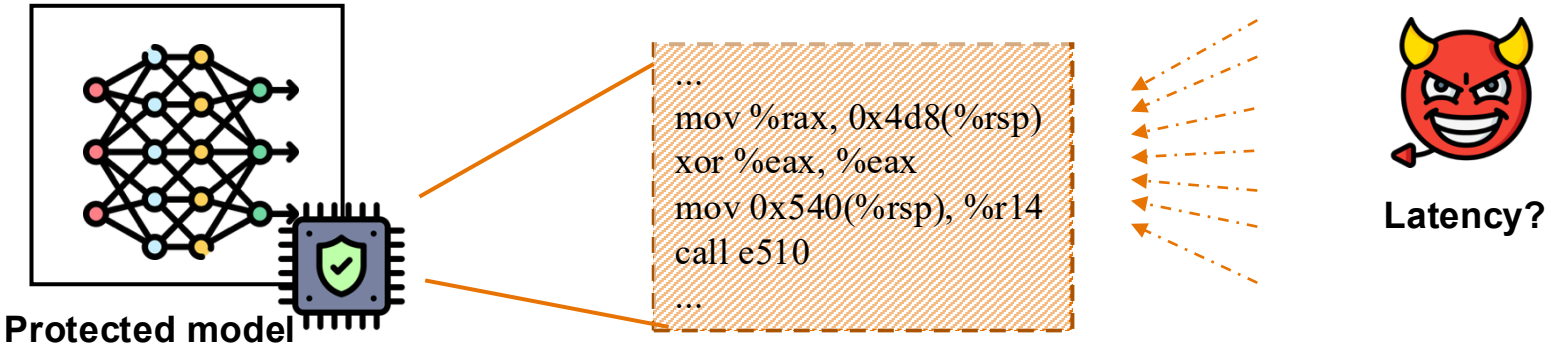

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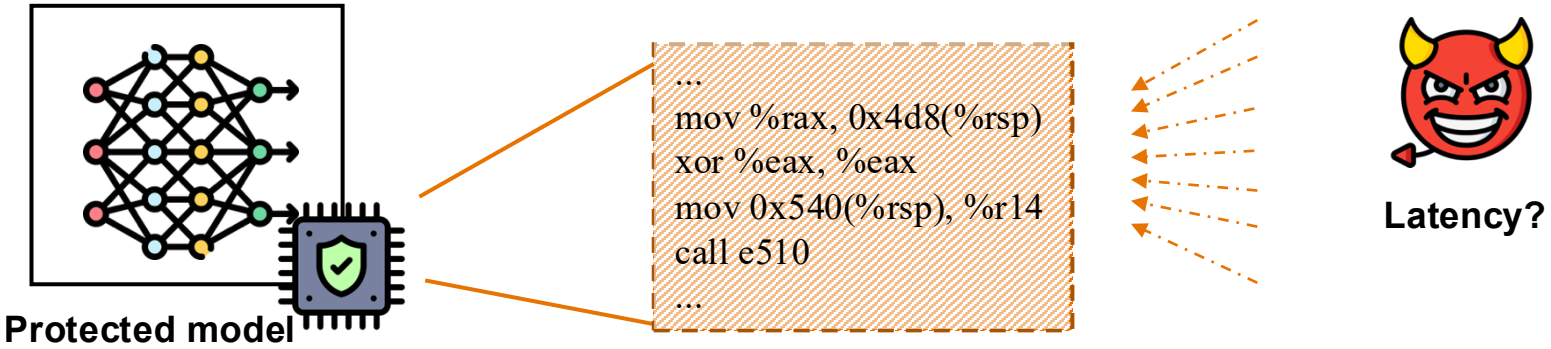

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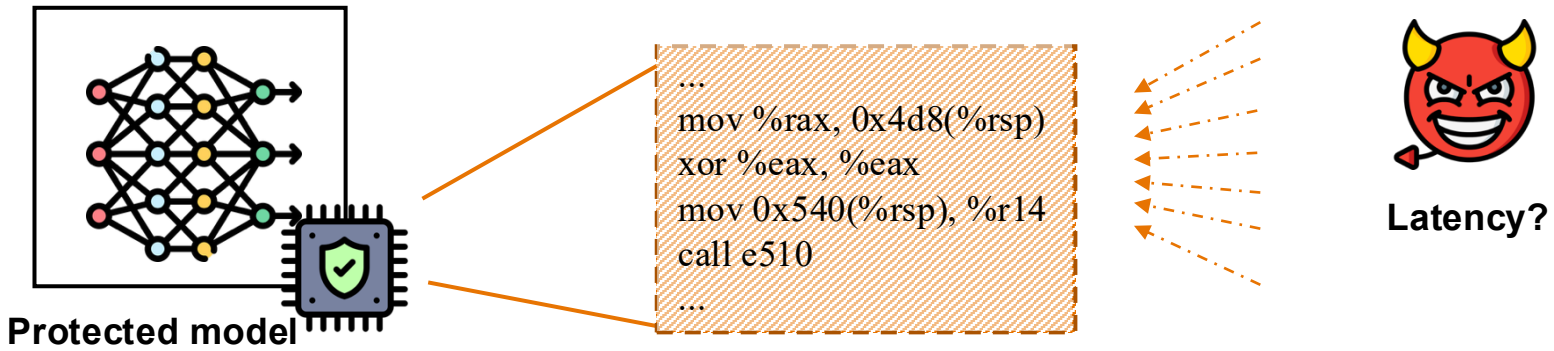

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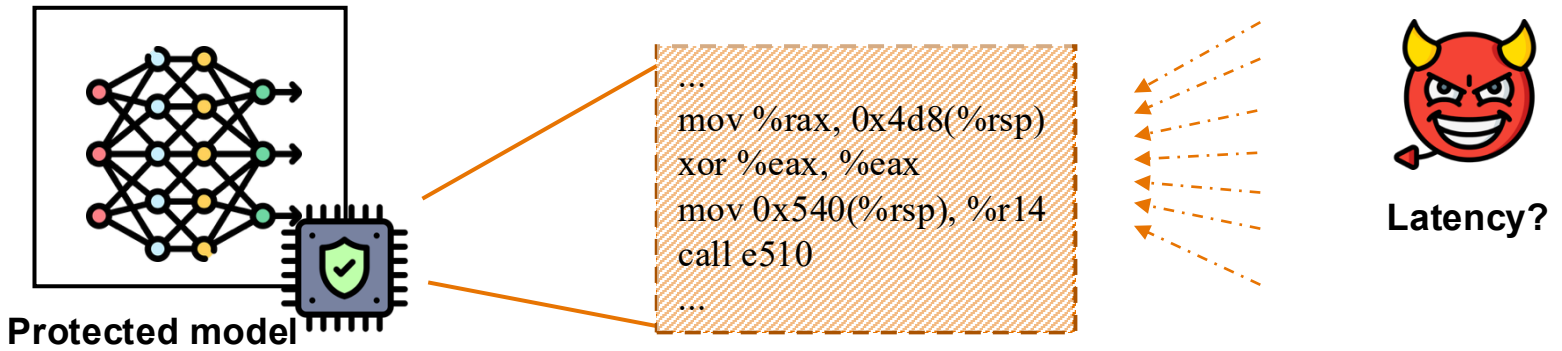

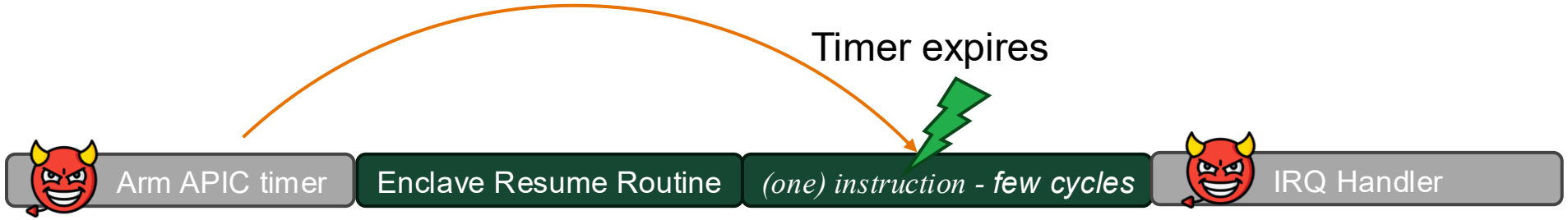

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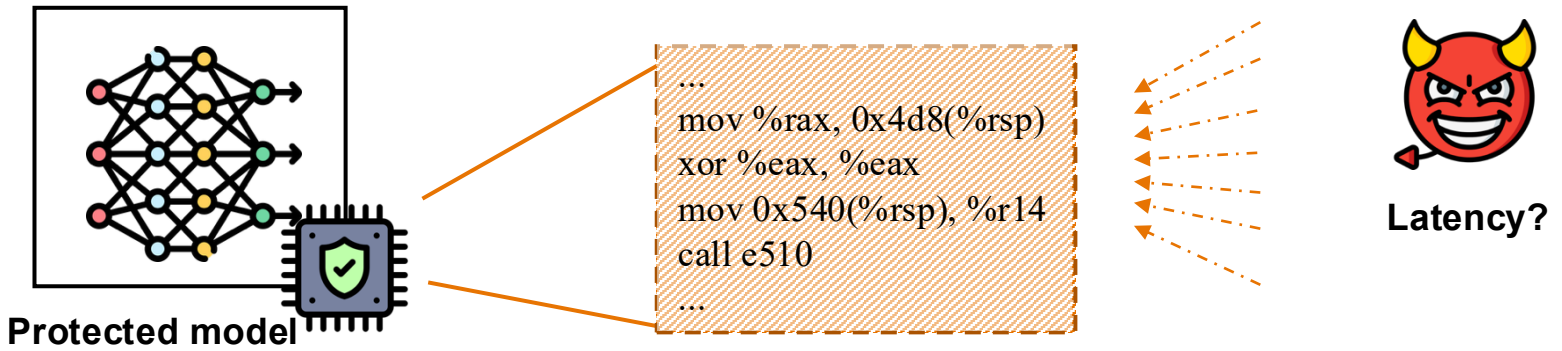

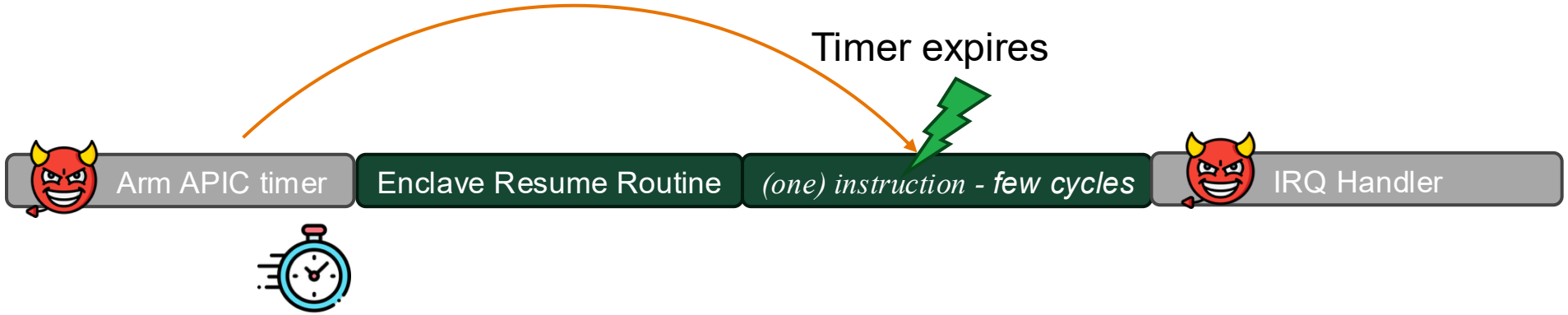

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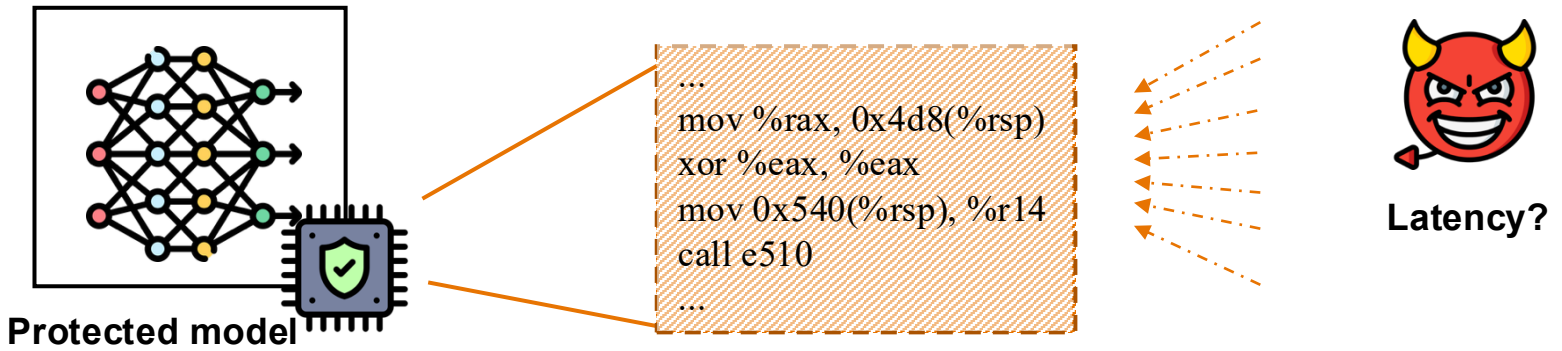

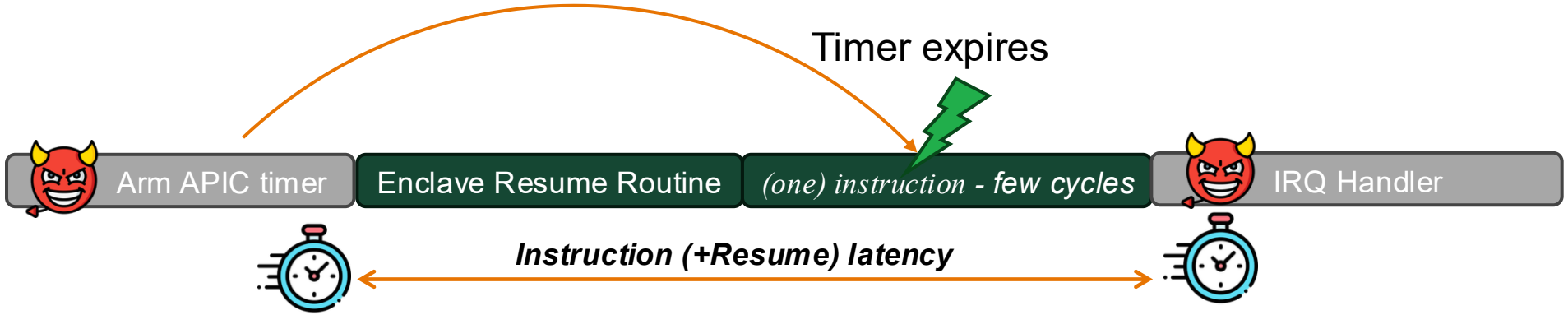

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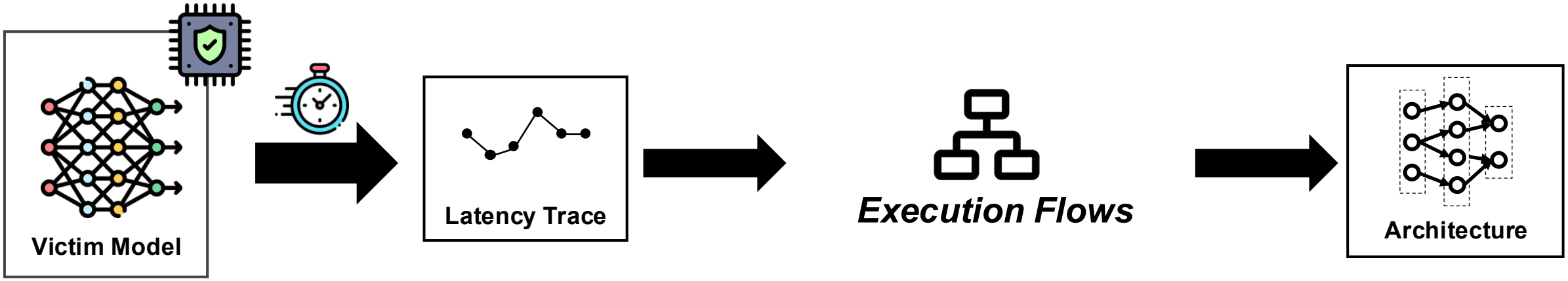

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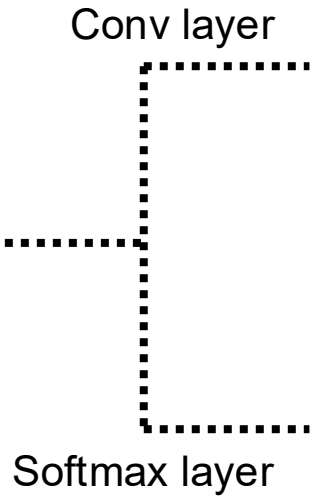

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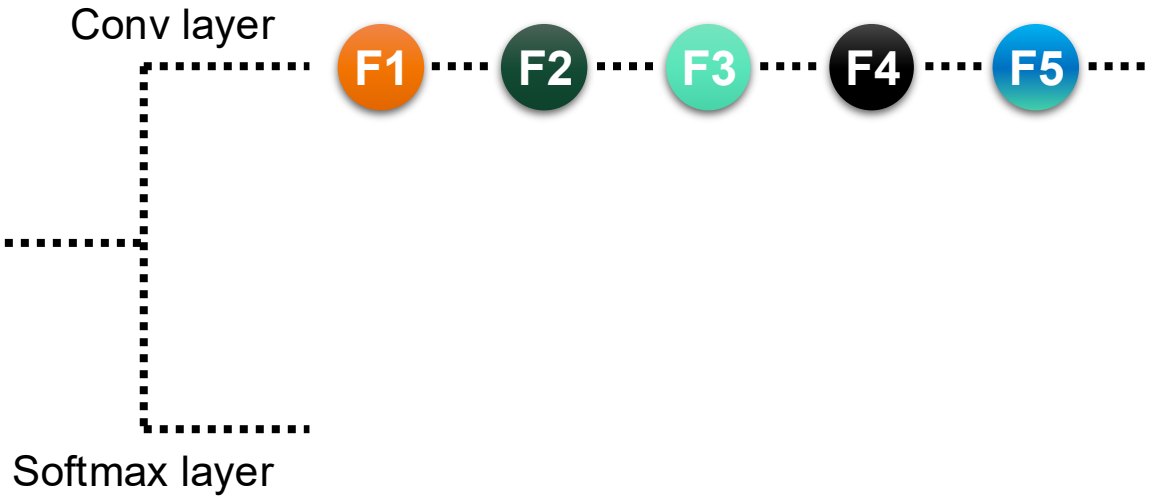

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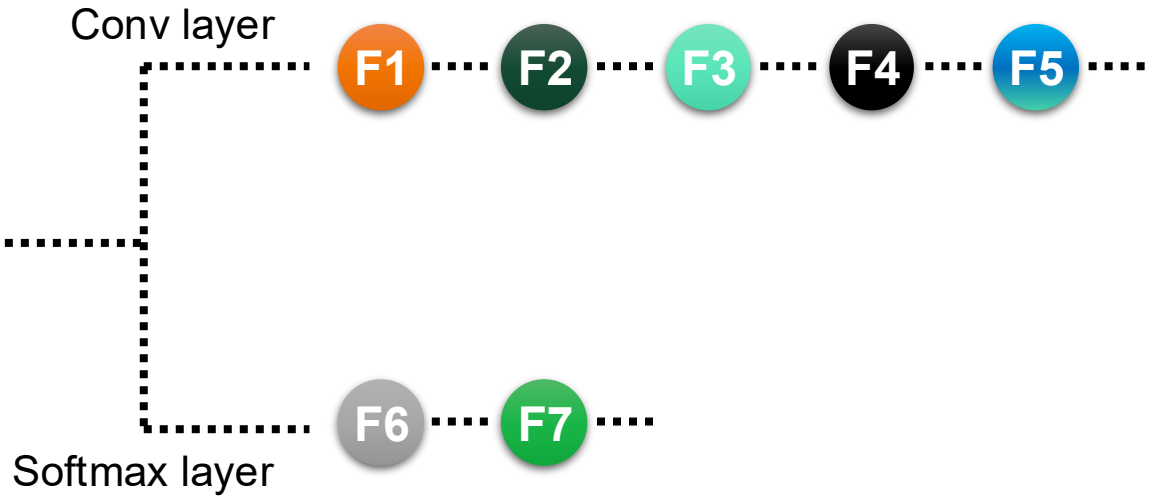

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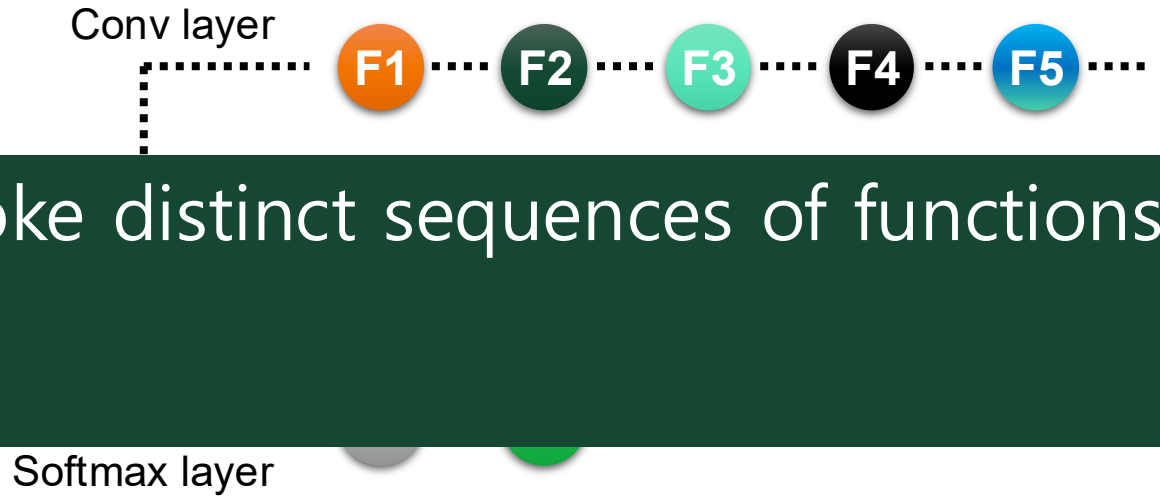

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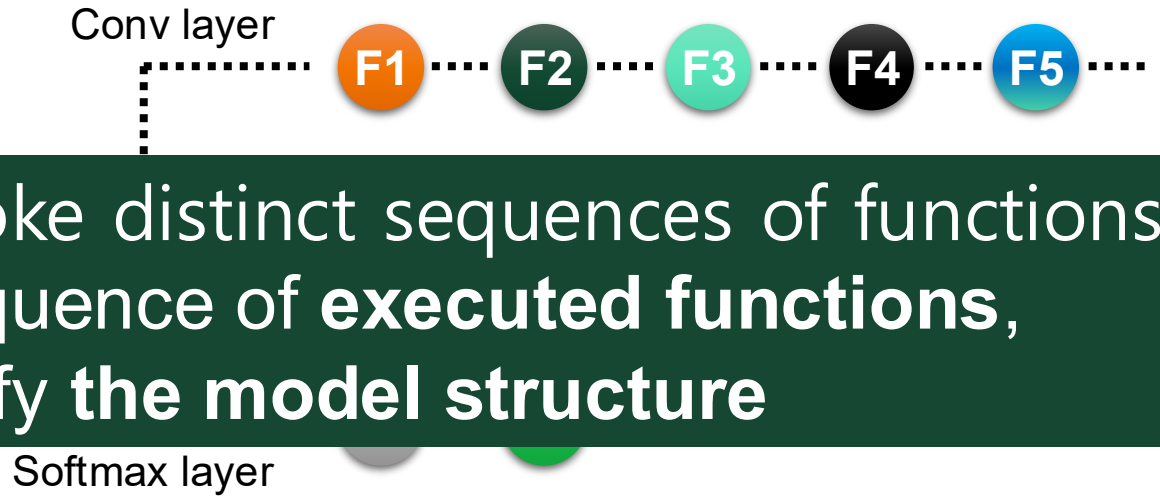

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Code example in Tensorflow Lite (2)

- Certain hyperparameters influence a control flow
  - e.g., the number of loop iterations or a branch taken

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inline void Conv(...)
{
  for (int i = 0; i < filter_height; ++i)
    for (int j = 0; j < filter_width; ++j)
      for (int k = 0; k < input_depth; ++k) {
         float iv = input_data[Offset(...)];
         float fv = filter_data[Offset(...)];
         total += (input_value * filter_value);
      }
   }
}
```

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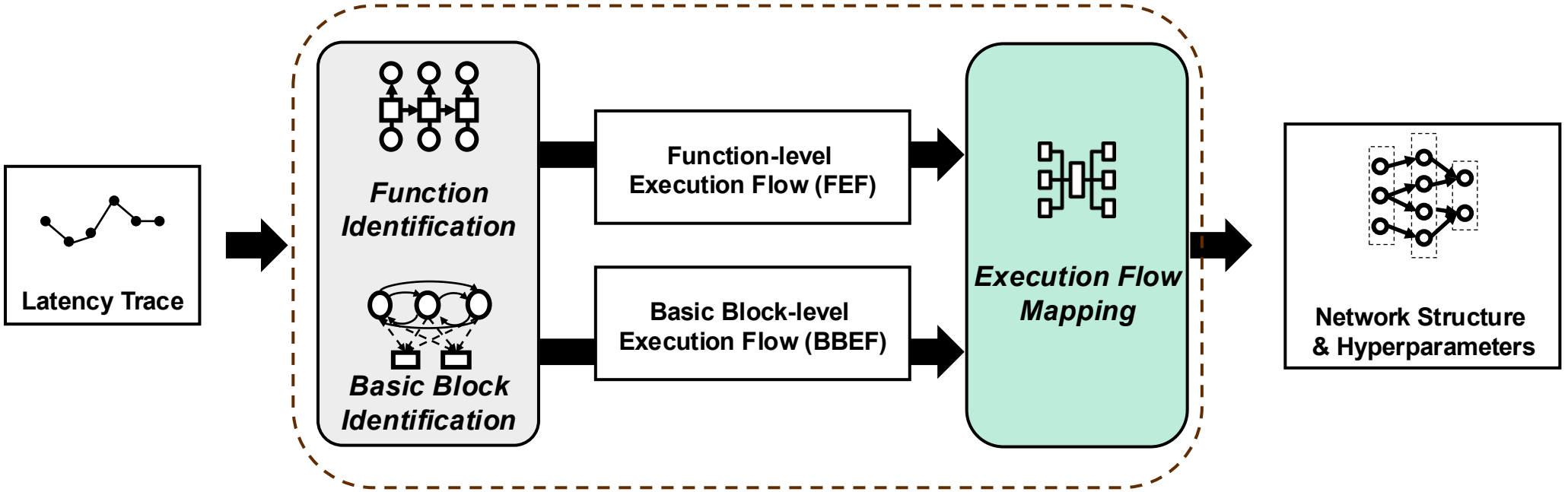
*Basic Block? A sequence of instructions w/
- a single entry at the beginning and
- a single exit at the end

Execution Flow Identification



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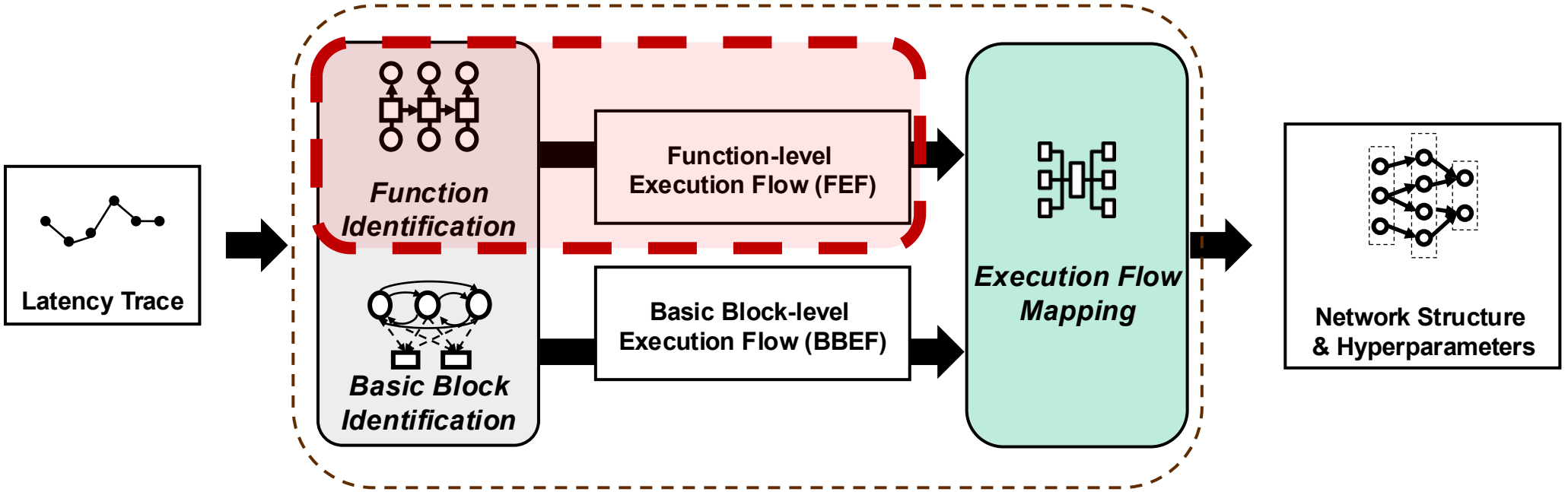

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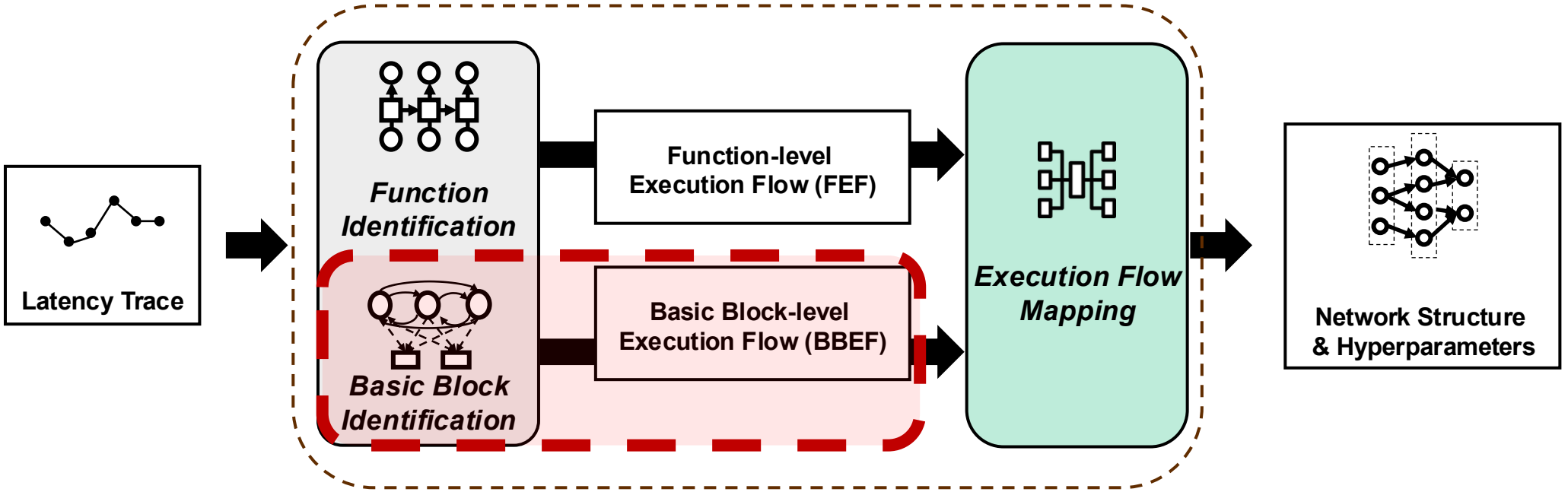

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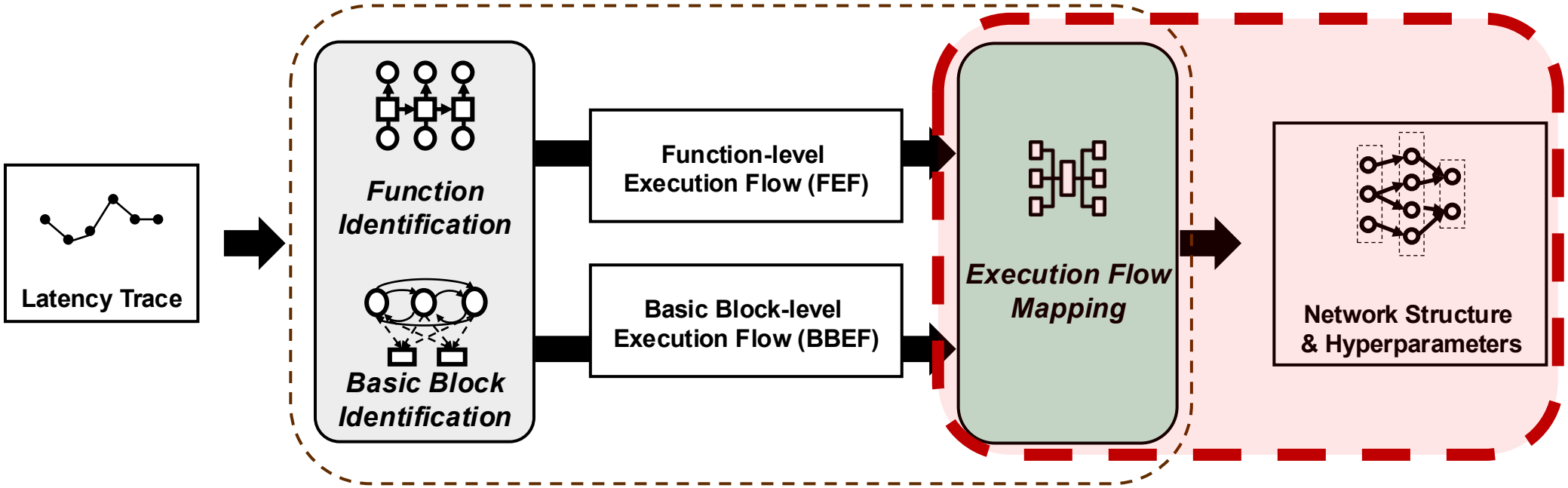

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- Identifying basic block-level execution flows (BBEFs)
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- Mapping the FEFs and BBEFs to architecture details

Identifying FEF

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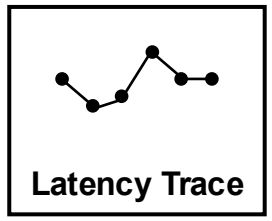

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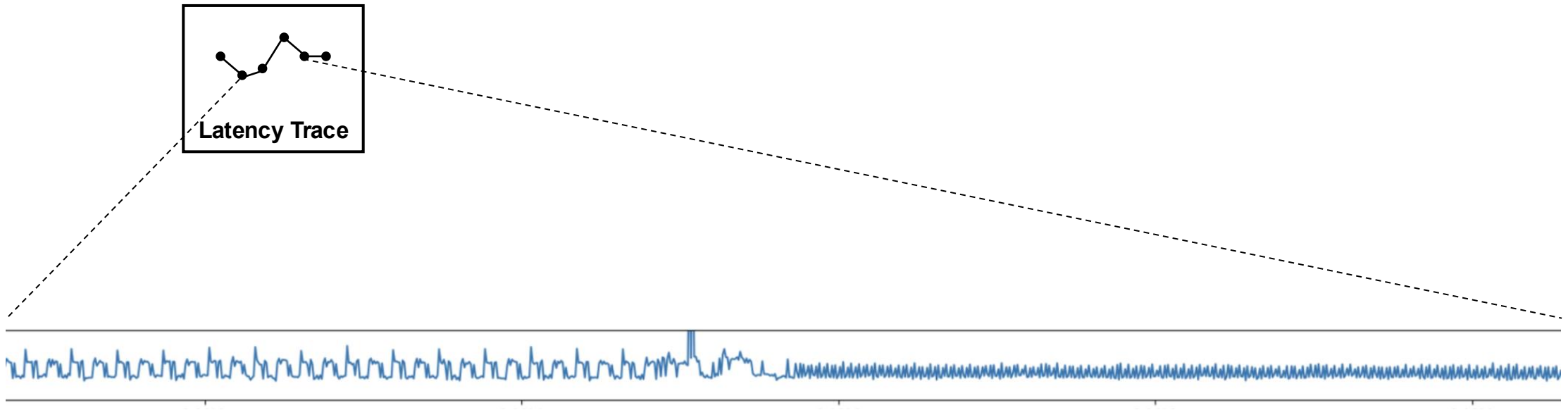

[A segment of latency trace]

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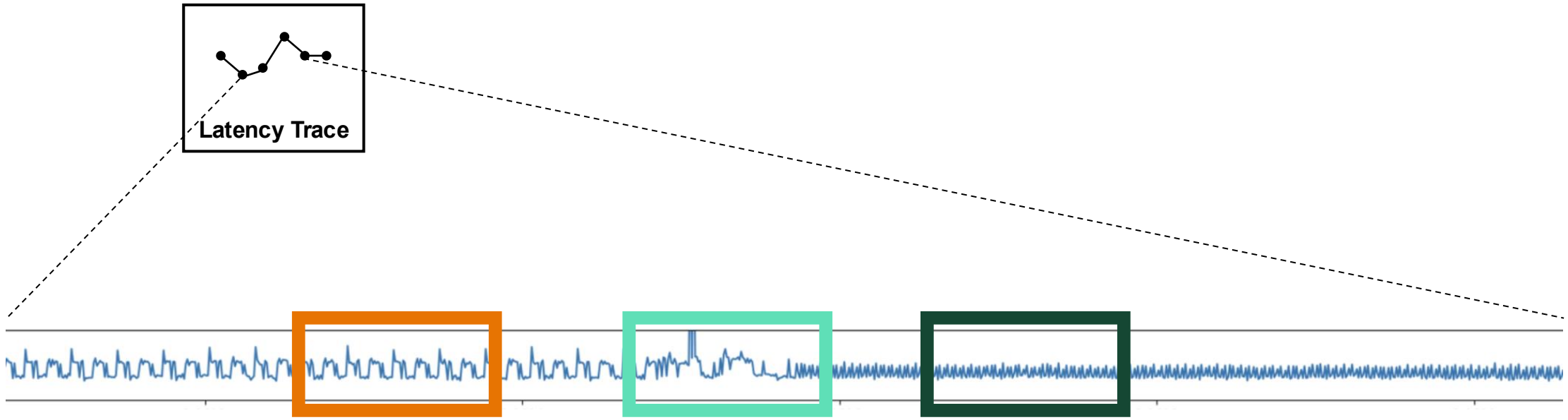

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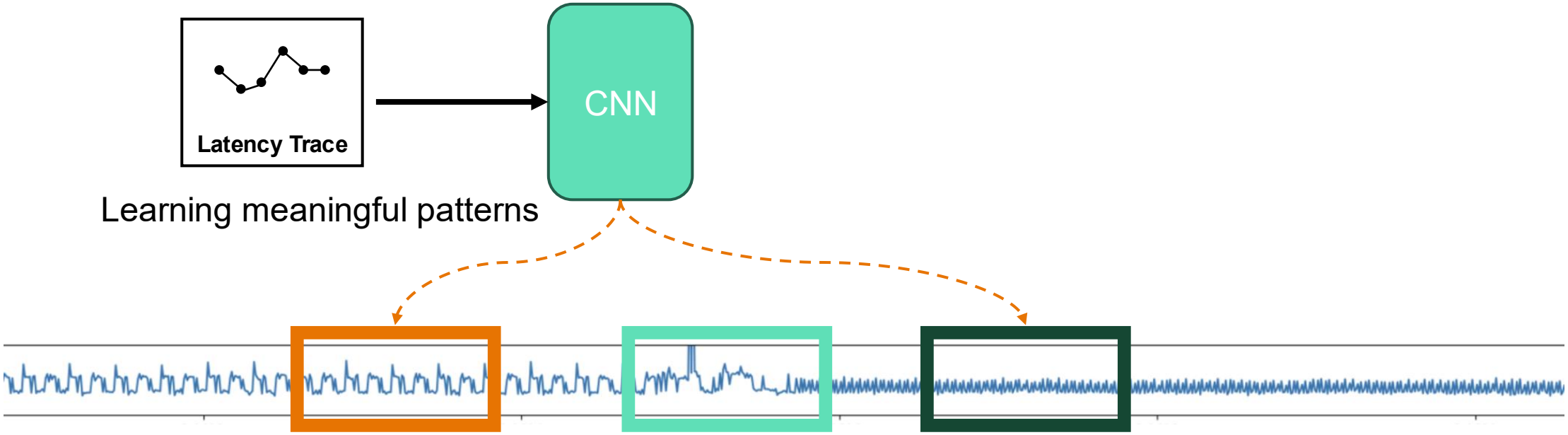

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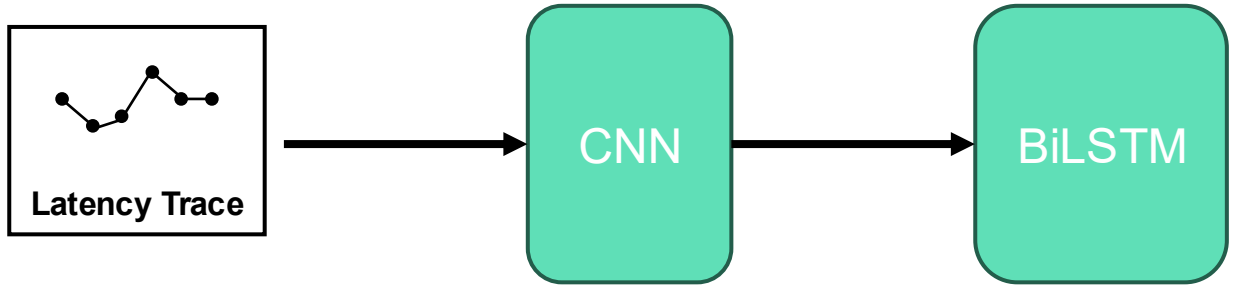
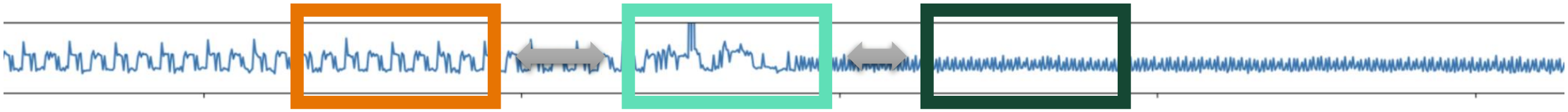


Learning sequential relationship



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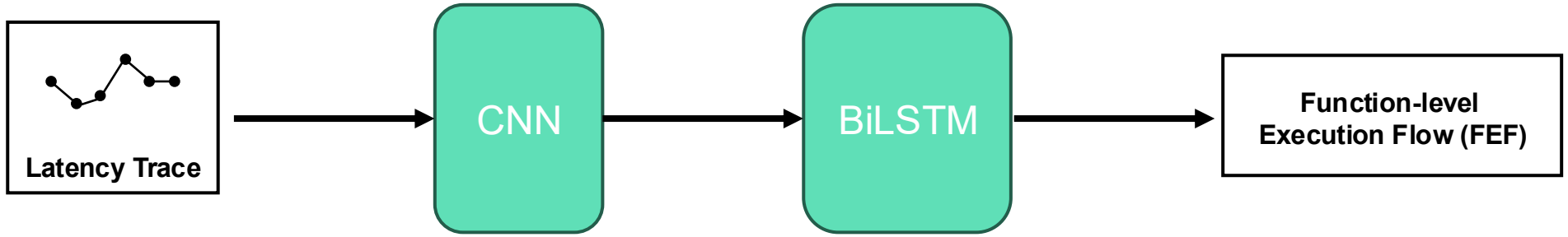

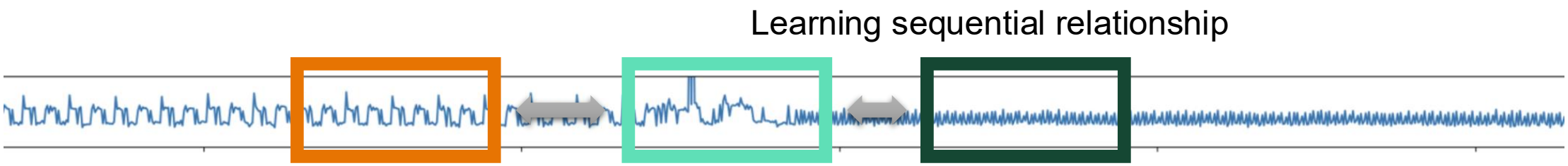

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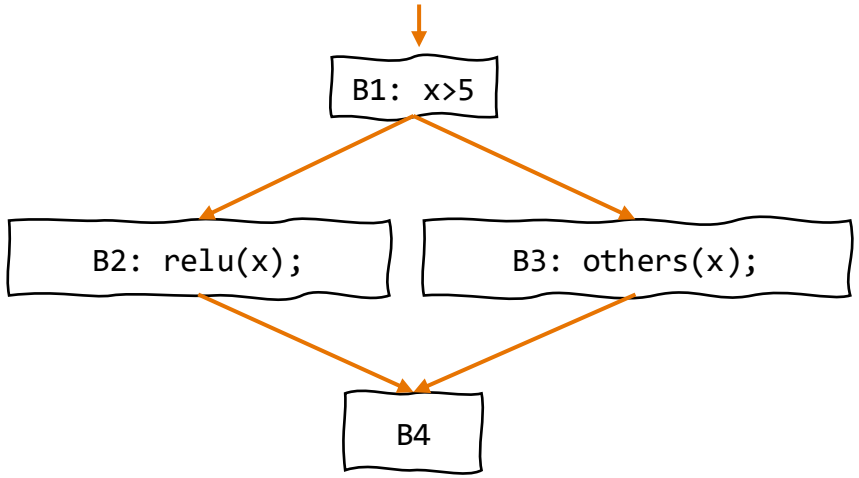

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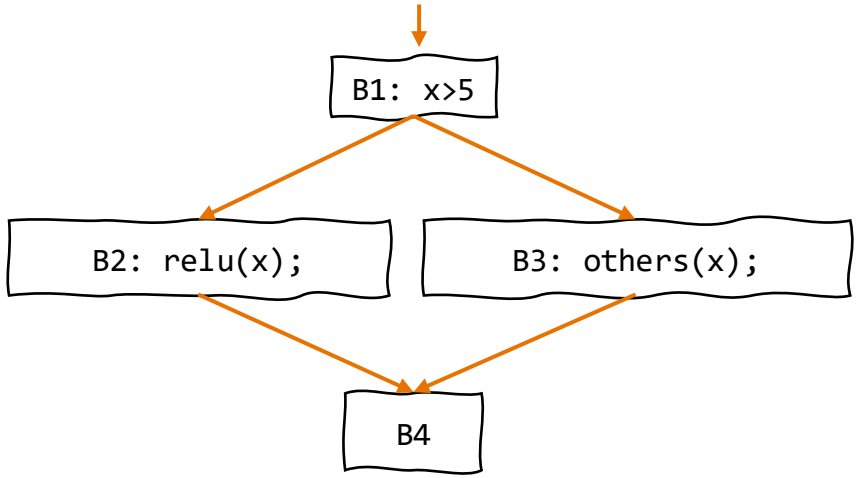
  if (is_relu)
    relu(x);
  else
    others(x);
  ...
}
```



Identifying BBEF

- Semi Hidden Markov Model (SHMM) represents control flows as a probabilistic model

```
{
  ...
  if (is_relu)
    relu(x);
  else
    others(x);
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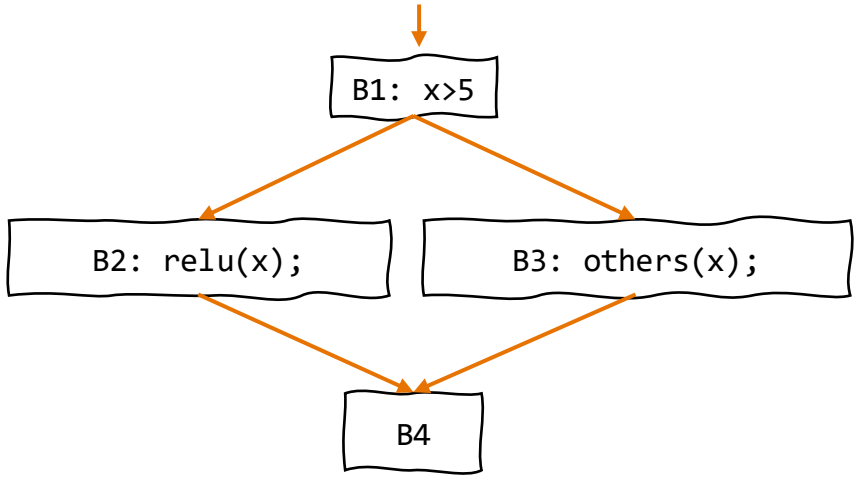
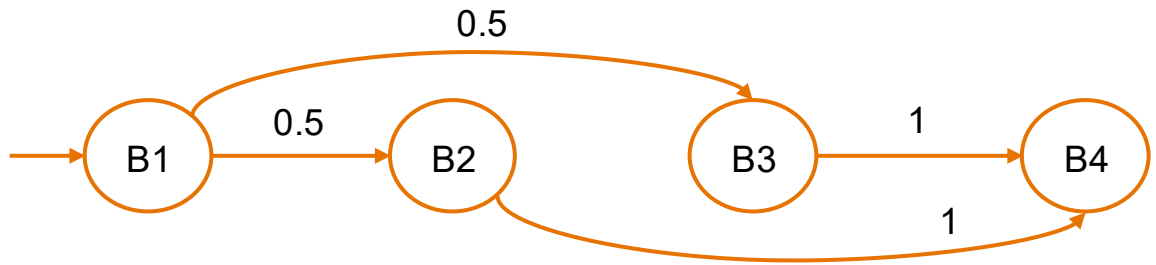
```





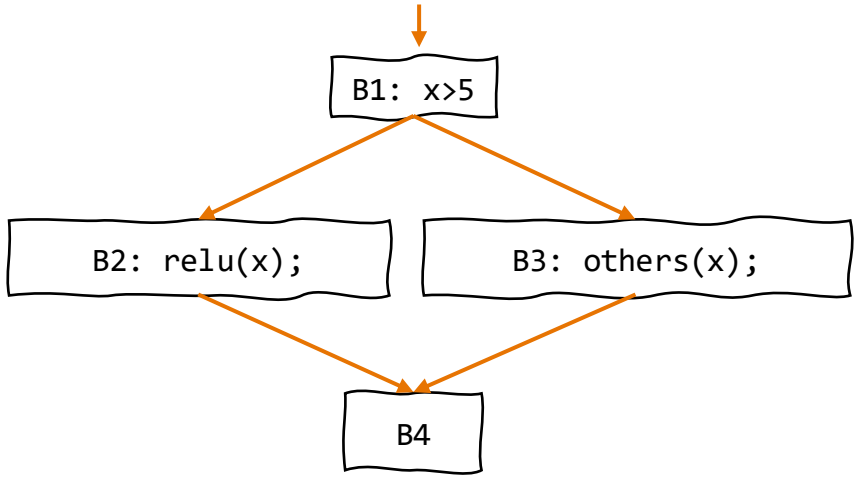
Markov Model

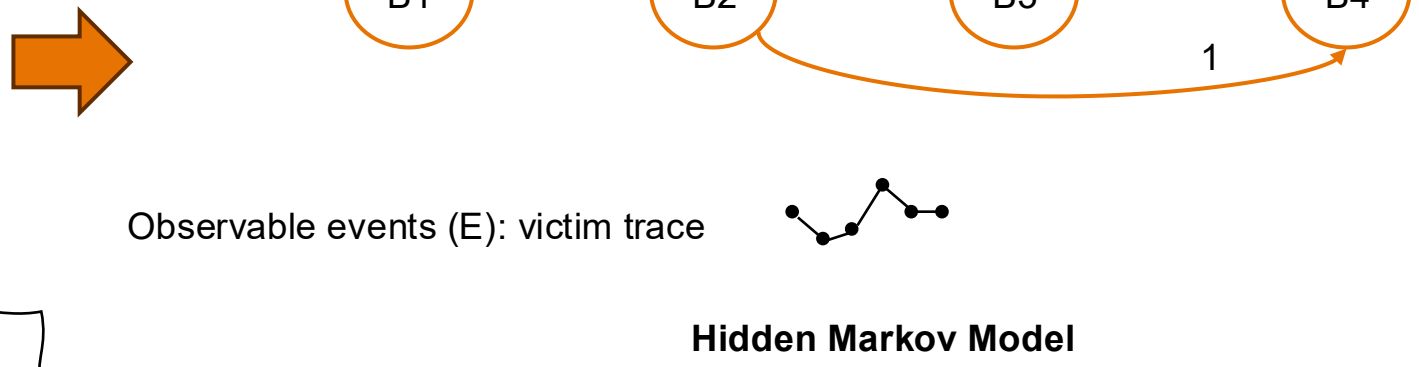
*Markov process? a process whose future state depends **only on** its present state*

Identifying BBEF

- Semi Hidden Markov Model (SHMM) represents control flows as a probabilistic model

```
{
  ...
  if (is_relu)
    relu(x);
  else
    others(x);
  ...
}
```



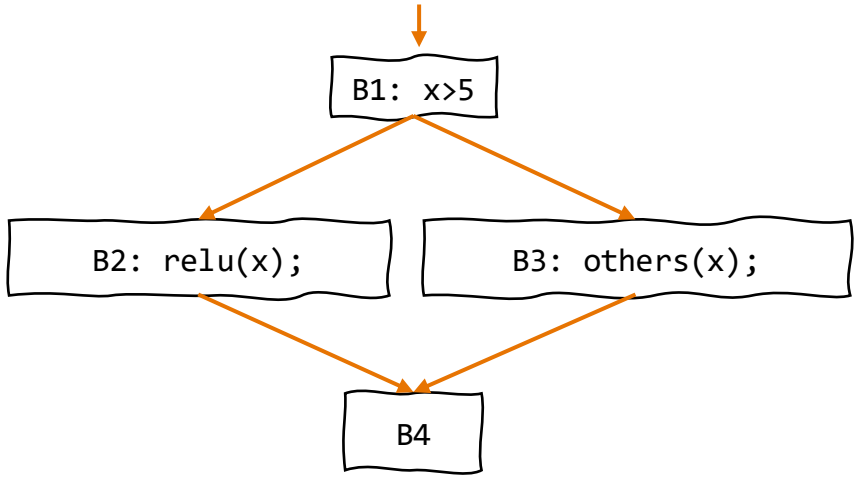


Hidden Markov Model

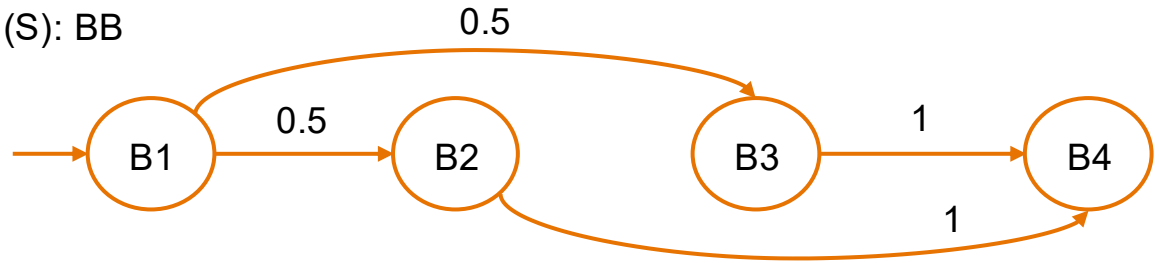
Identifying BBEF

- Semi Hidden Markov Model (SHMM) represents control flows as a probabilistic model

```
{
  ...
  if (is_relu)
    relu(x);
  else
    others(x);
  ...
}
```



Hidden states (S): BB



Observable events (E): victim trace

Hidden Markov Model

Emission probability: $P(E_x|S_i)$

Identifying BBEF

- Semi Hidden Markov Model (SHMM) represents control flows as a probabilistic model

```
{
  ...
  if (is_relu)
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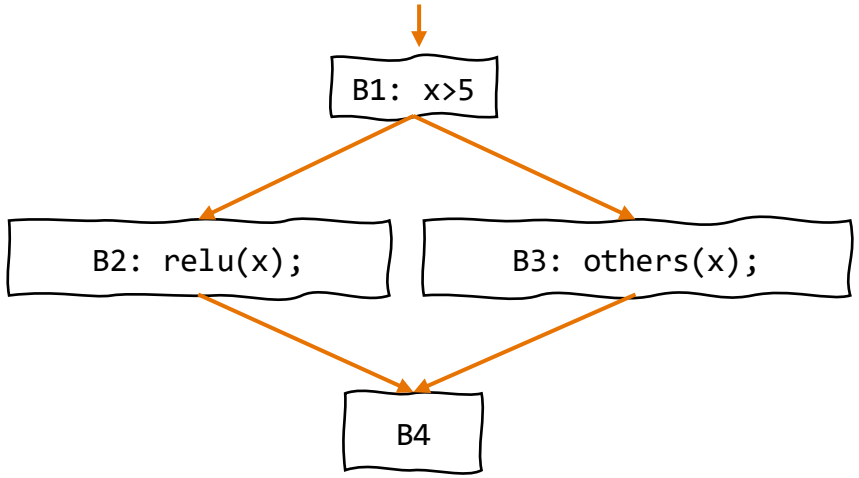
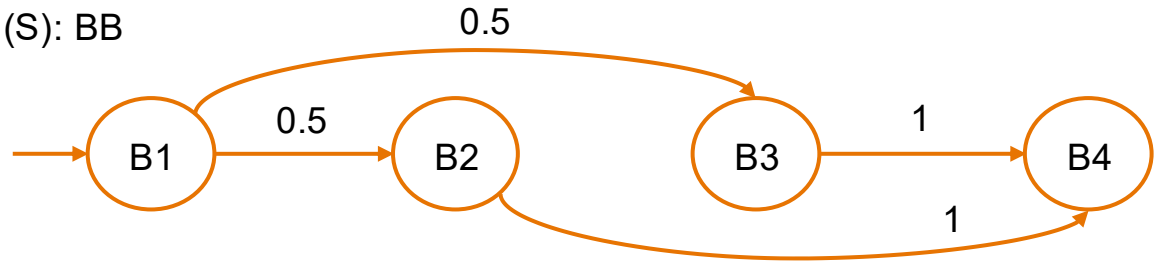


Hidden states (S): BB



Observable events (E): victim trace

Hidden Markov Model

Emission probability: $P(E_x|S_i)$ = Normalized Similarity

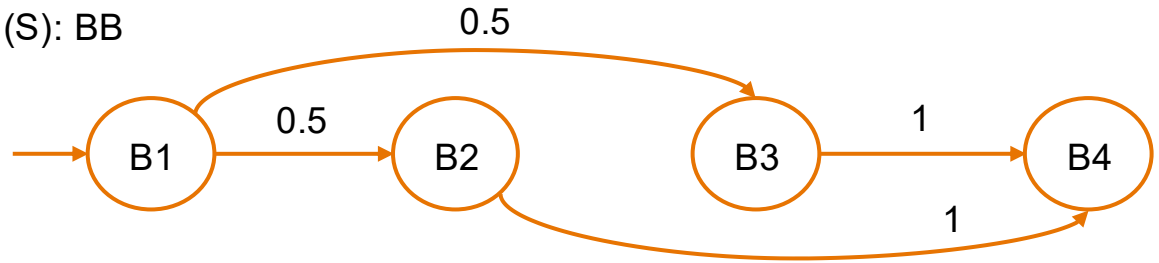
Identifying BBEF

- Semi Hidden Markov Model (SHMM) represents control flows as a probabilistic model

Reference Latency of B2

Reference Latency of B3

Hidden states (S): BB



Observable events (E): victim trace

Hidden Markov Model

Emission probability: $P(E_x|S_i)$ = Normalized Similarity

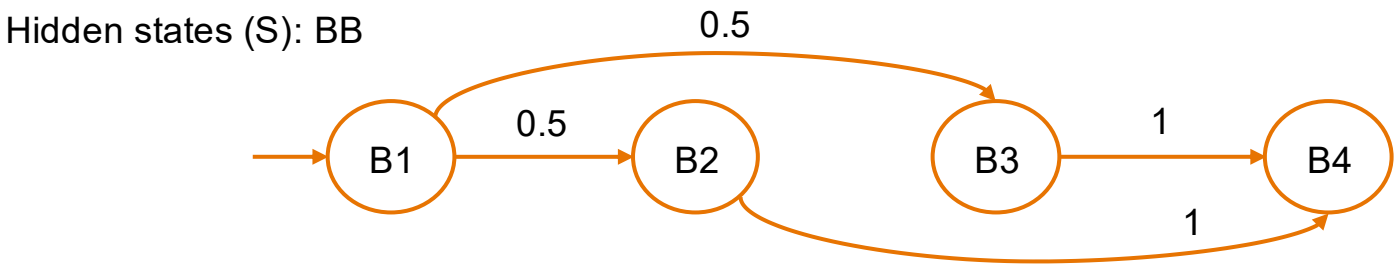
Identifying BBEF

- Semi Hidden Markov Model (SHMM) represents control flows as a probabilistic model

Victim Latency

Reference Latency of B2

Reference Latency of B3



Observable events (E): victim trace

Hidden Markov Model

Emission probability: $P(E_x|S_i)$ = Normalized Similarity

Identifying BBEF

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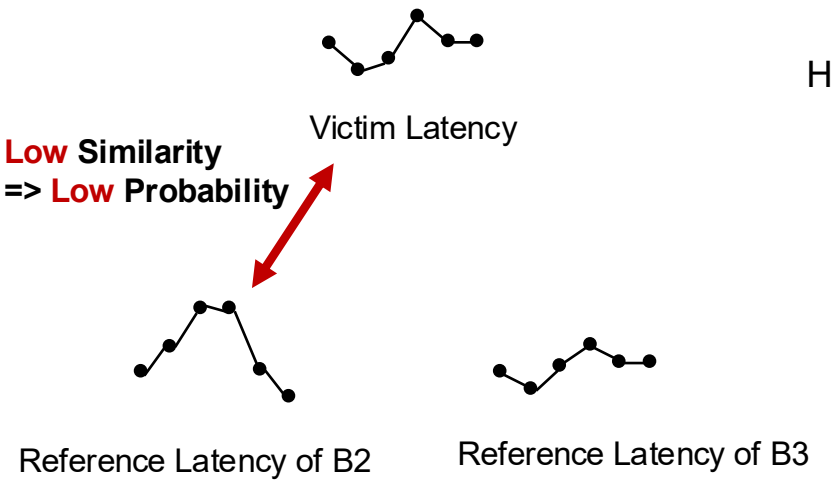
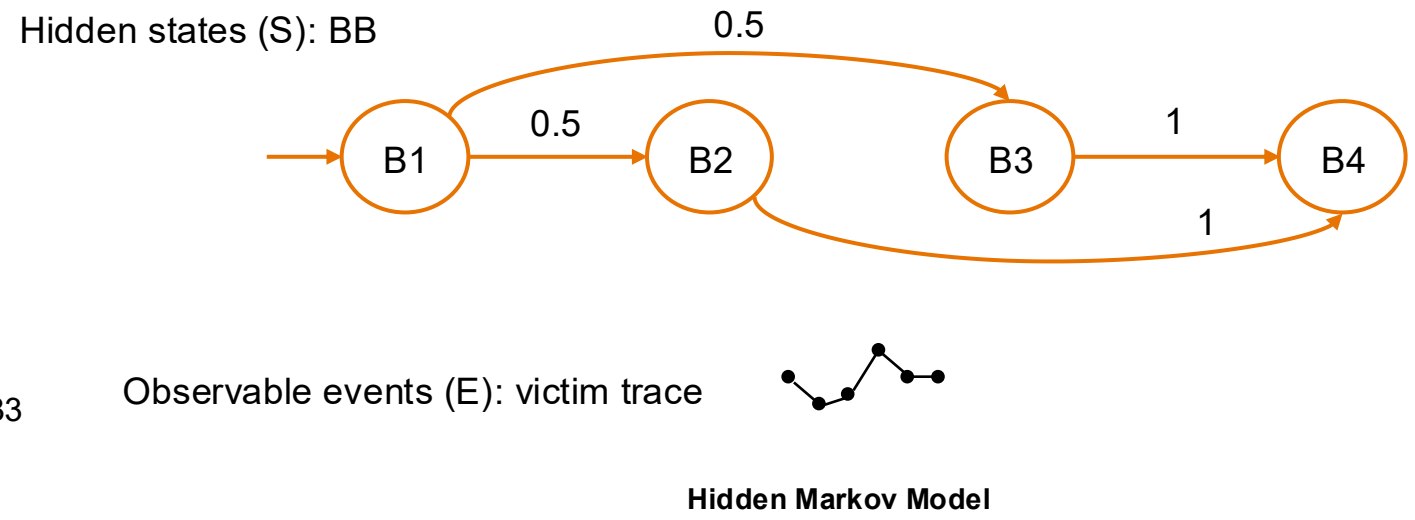
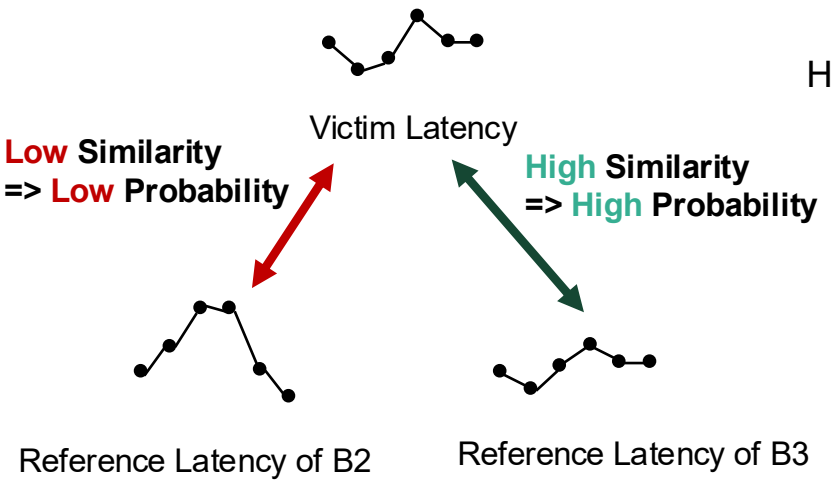


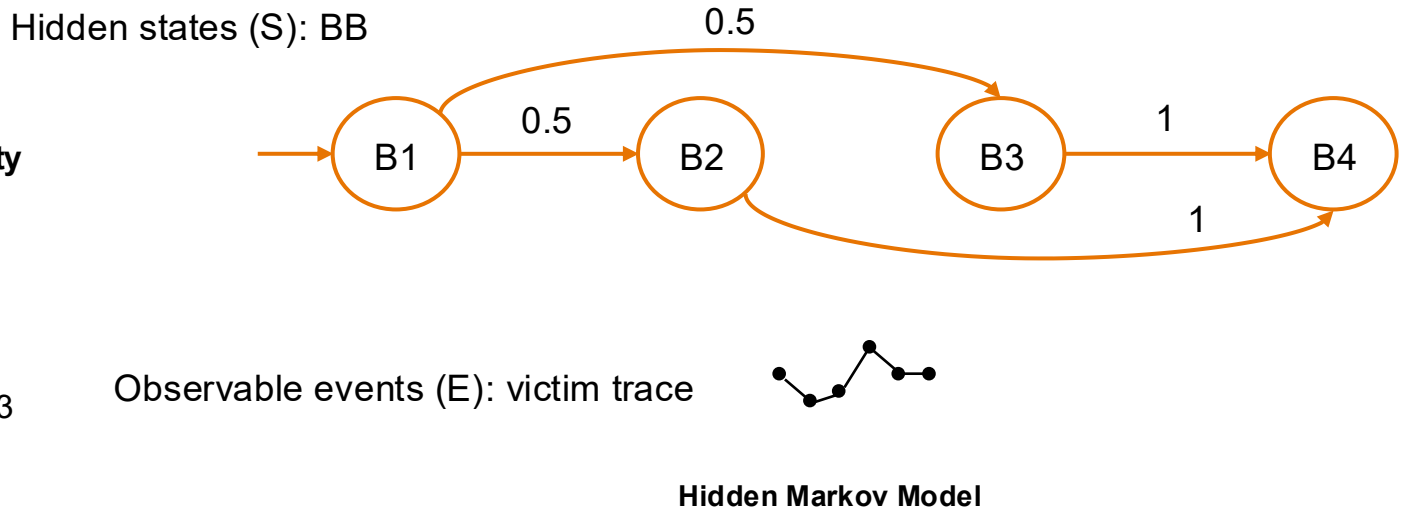


Emission probability: $P(E_x|S_i)$ = Normalized Similarity

Identifying BBEF

- Semi Hidden Markov Model (SHMM) represents control flows as a probabilistic model

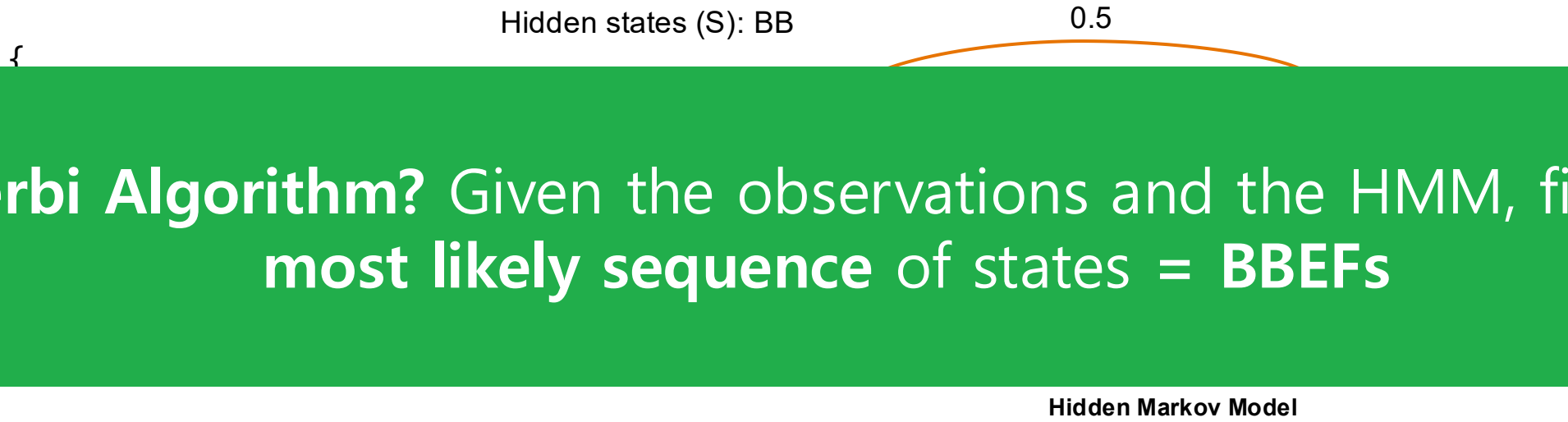




Emission probability: $P(E_x|S_i)$ = Normalized Similarity

Identifying BBEF

- Semi Hidden Markov Model (SHMM) represents control flows as a probabilistic model



Viterbi Algorithm? Given the observations and the HMM, find **the most likely sequence** of states = **BBEFs**

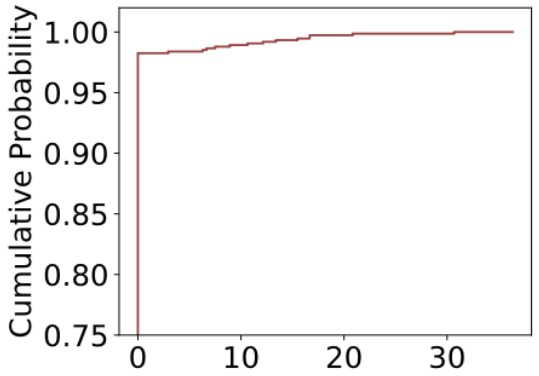
Hidden Markov Model

Emission probability: $P(E_x|S_i)$ = Normalized Similarity

Evaluation: Overview

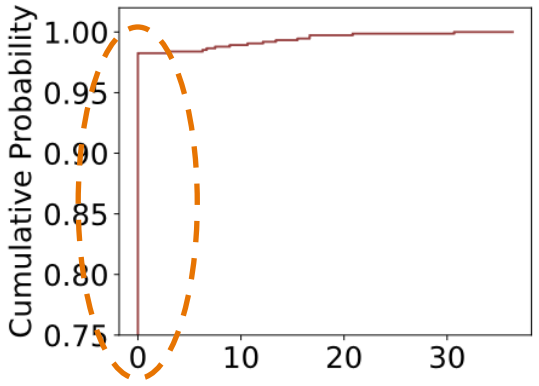
- Setup
  - Intel Core i7-10700 CPU with SGX support
- 3 libraries/frameworks
  - **Darknet**, Tensorflow Lite, ONNX runtime
- 100 random DNN models are tested
  - 24 predefined layer combinations from 10 layer types
    - Convolutional, FC, activation, maxpool, avgpool, softmax, etc.
  - Hyperparameters are randomly chosen
    - #filters, filter size, activation function type, stride, padding, etc.

Evaluation result: Accuracy



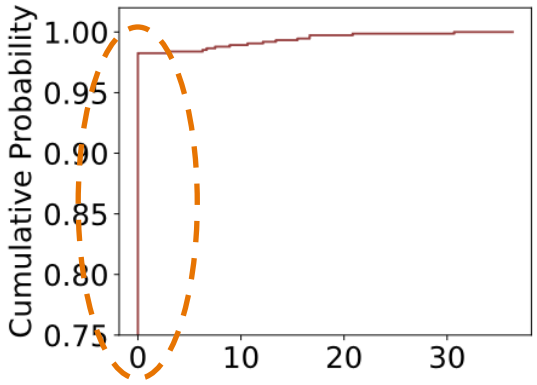
Error rate of Identified FEFs

Evaluation result: Accuracy

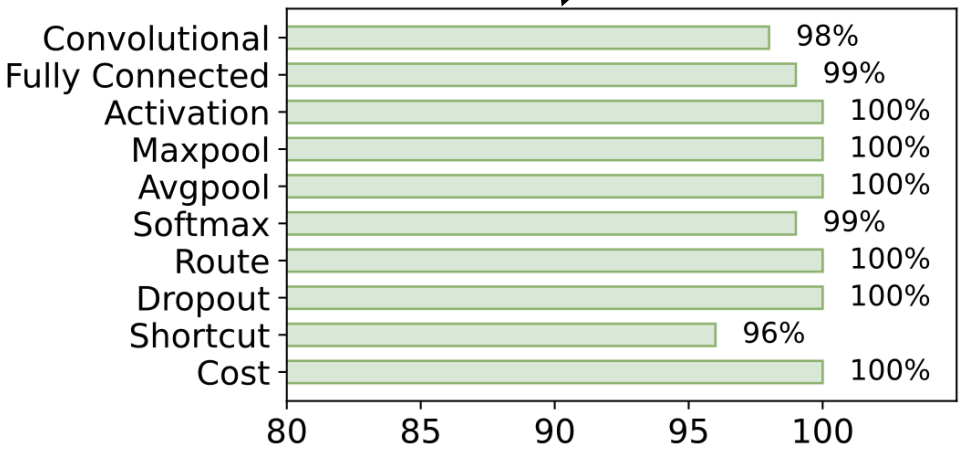


Error rate of Identified FEFs

Evaluation result: Accuracy

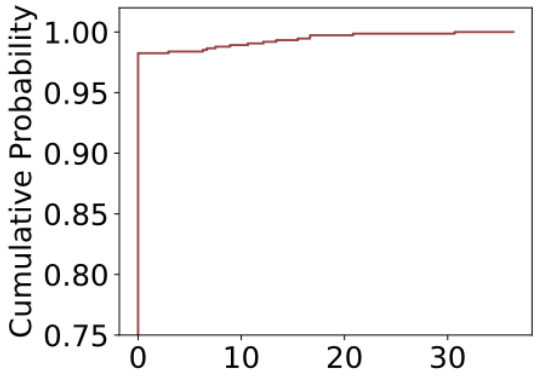


Error rate of Identified FEFs

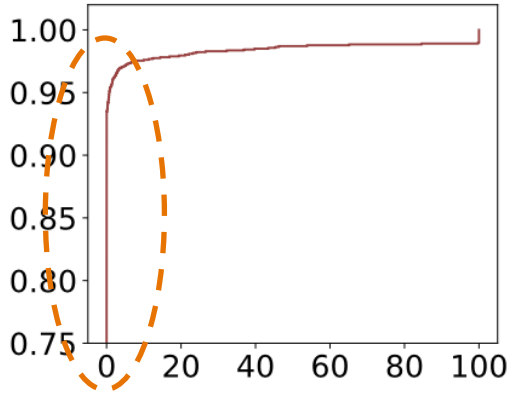


Accuracy of recovered layer types

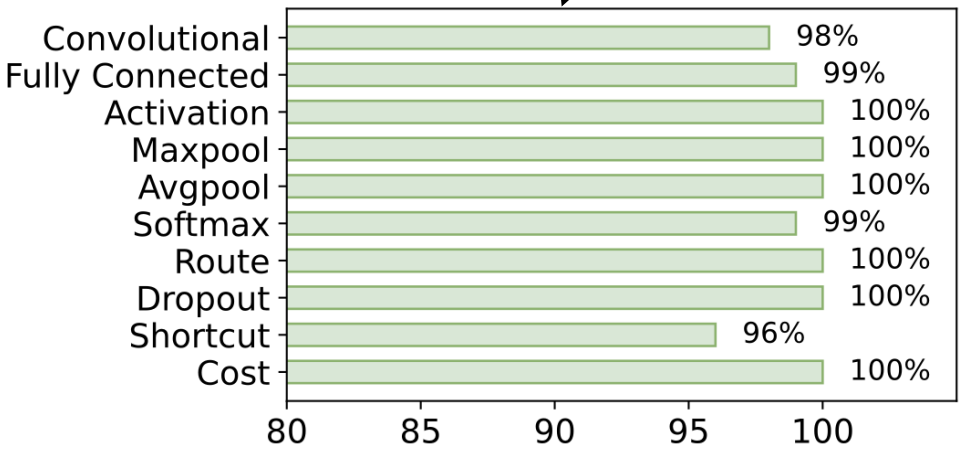
Evaluation result: Accuracy



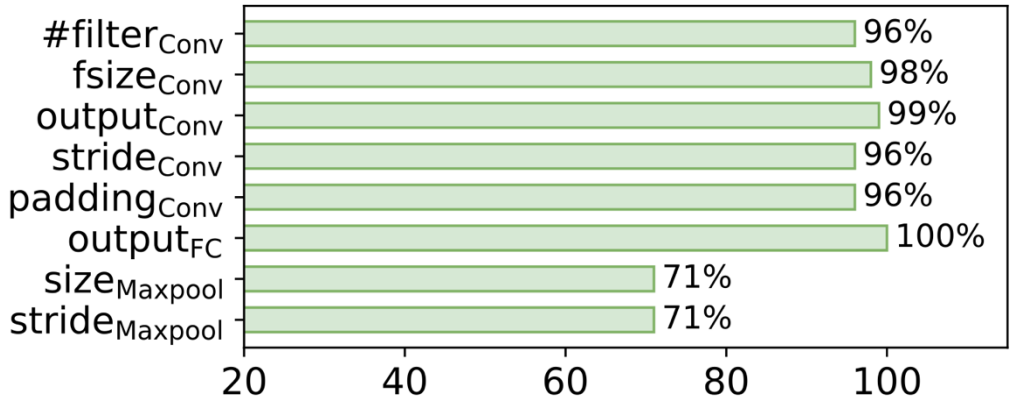
Error rate of Identified FEFs



Error rate of Identified BBEFs

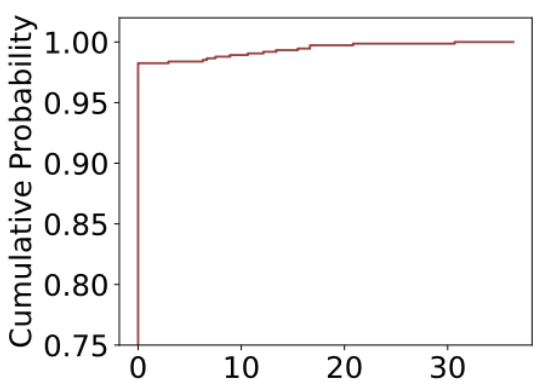


Accuracy of recovered layer types

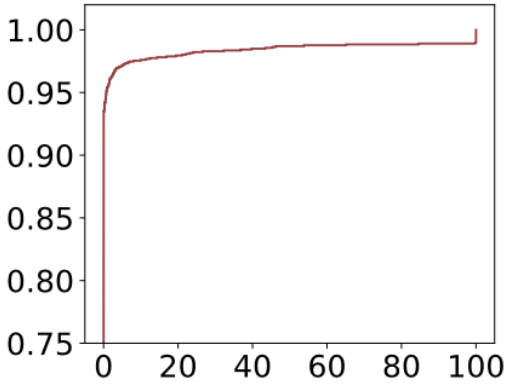


Accuracy of recovered HPs

Evaluation result: Accuracy

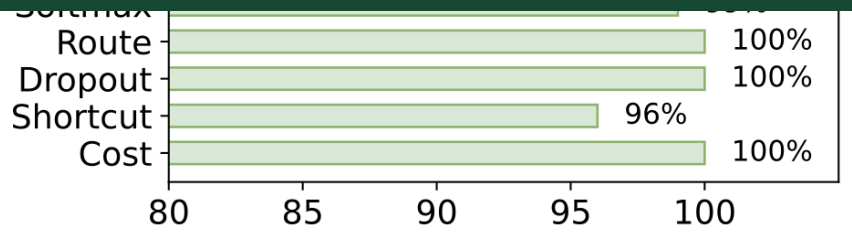


Error rate of Identified FEFs

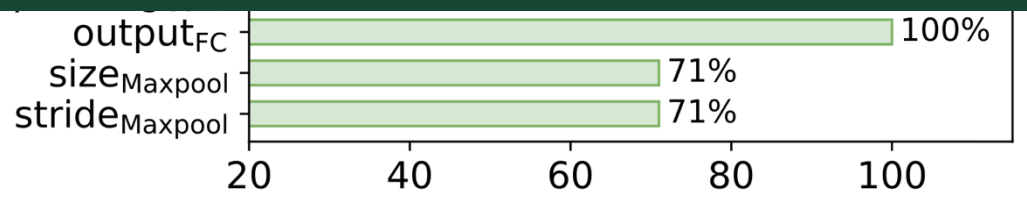


Error rate of Identified BBEFs

Accurate identification of FEFs and BBEFs leads to high accuracy in extracting architecture details



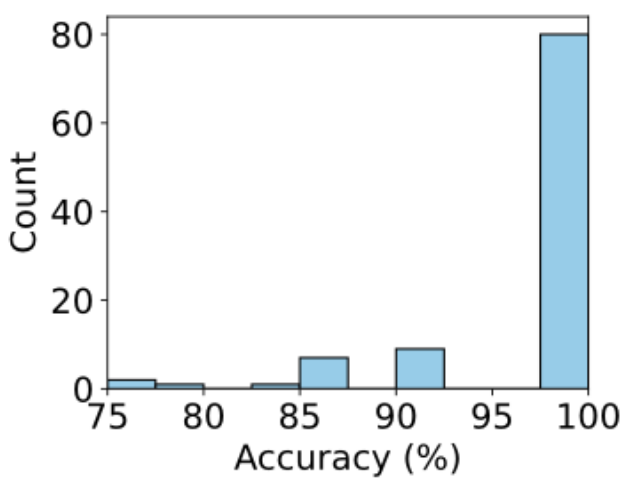
Accuracy of recovered layer types



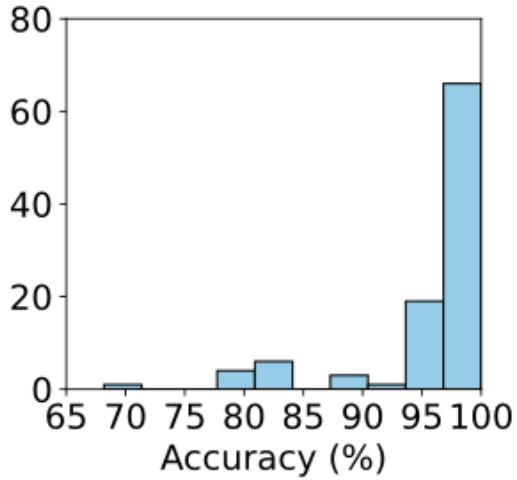
Accuracy of recovered HPs

Evaluation result: Attack accuracy

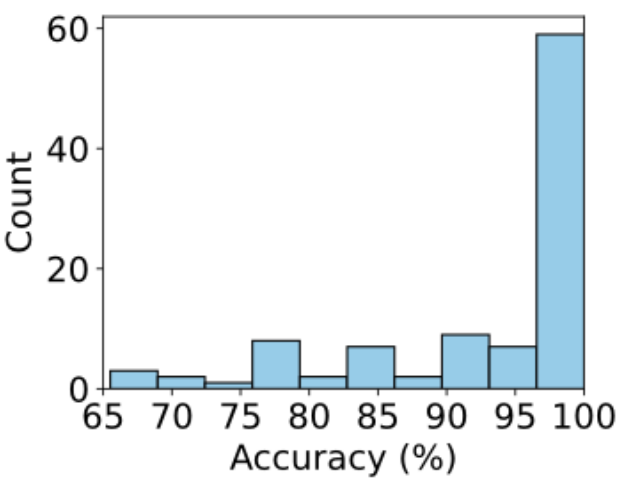
- High attack accuracy
  - Metric = #identified components/#total components
  - Average: 97%, 96%, and 94%, respectively



Darknet



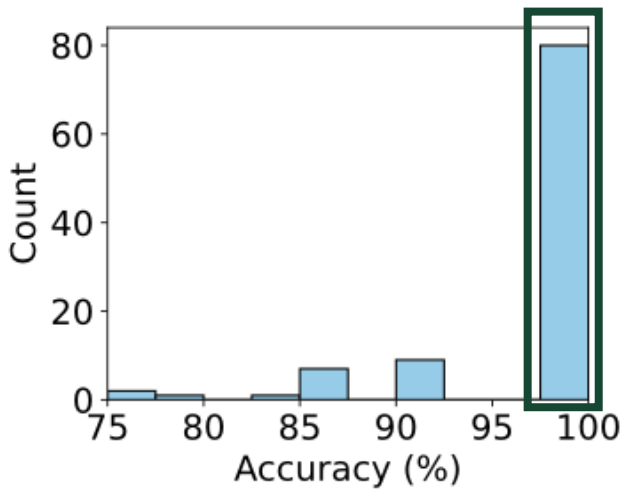
TF Lite



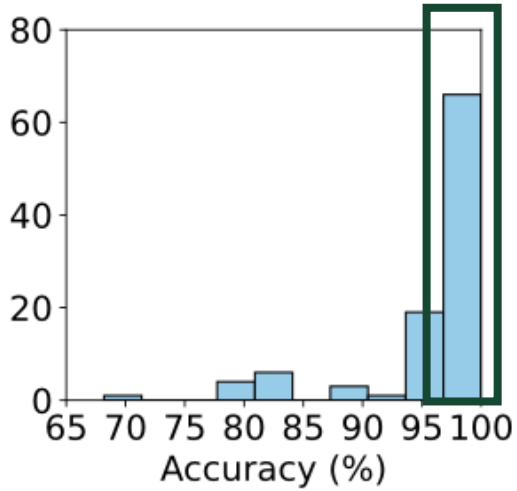
ONNX Runtime

Evaluation result: Attack accuracy

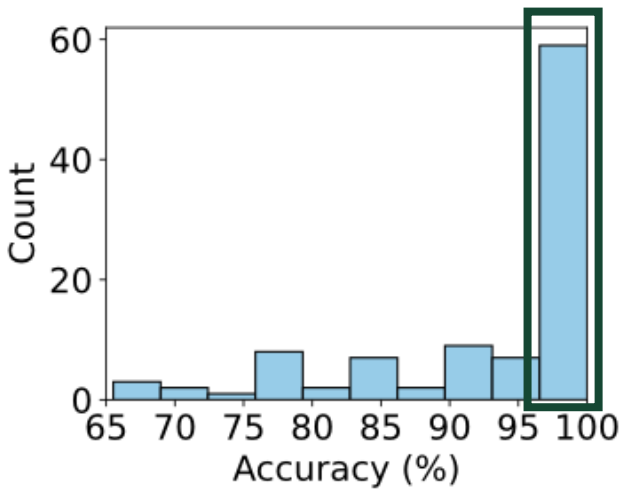
- High attack accuracy
  - Metric = #identified components/#total components
  - Average: 97%, 96%, and 94%, respectively



Darknet



TF Lite



ONNX Runtime

Conclusion

- **DLS** extracts a DNN architecture from latency traces
- To bridge the trace–architecture gap, DLS reconstructs execution flows and maps them to architectural details
  - Function-level execution flows (FEF) via CNN-LSTM
  - Basic block-level execution flows (BBEF) via SHMM
- High attack accuracy (>94%) demonstrates practical effectiveness

Thank you!

Supported by